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Explicit and Implicit Aspect Extraction using Whale Optimization Algorithm and Hybrid Approach

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***Abstract*— Huge volume of reviews by customers published on different products websites has become an important source of information for both customers and companies. Customers require the information to help them in decision making for buying products, while companies analyze these reviews to improve their products. However, reading and analyzing huge amount of reviews manually are impossible and cumbersome. Thus, an automatic technique known as sentiment analysis or opinion mining has been used to analyze these reviews and extract the relevant information according to different users' needs. The growth of sentiment analysis has resulted in the emergence of various techniques for explicit aspect extraction and implicit aspect extraction. In this paper, we proposed new approaches for both explicit and implicit aspect extraction. For explicit aspect extraction, we proposed to use Whale Optimization Algorithm (WOA) for selecting the best dependency relation patterns from the list of hand-craft patterns with the help of web based similarity. As for the implicit aspect extraction, we proposed a hybrid approach based on the use of corpus co-occurrence, dictionary-based, and web based similarity. To measure the performance of the proposed approaches, the approaches will tested and evaluated using standard datasets and will be compared to other baseline methods.**

Keywords—explicit aspect; implicit aspect; rule patterns; rule pattern selection

I. INTRODUCTION

Due to the wide internet spreading and the emergence of various online commercial websites like Amazon.com, Zalora.com and Agoda.com, the customers buying attitudes has changed tremendously. There is also high percentage of the e-commerce websites which allow users to post reviews about the products or services they purchase based on their experiences. These reviews become a source of interest by many sectors such as individual customers, and companies. Reading and analyzing these reviews by individual customers can help them in decision making for buying any products. For the companies, these reviews are very important to help the management to find the defects in their products based on the feedback given by the customers. In addition, they can also use the reviews given by the customers to improve their products or services. However, the problem arises as the reviews volume increases rapidly within seconds, which in turn make it impossible to either the companies or the individual customers to read all available review, analyze it, and extract the relevant information. Thus, an automatic technique known as sentiment analysis or opinion mining has been used to analyze these reviews and extract the relevant information according to different users' needs. Sentiment analysis or opinion mining is a classification process that extract the opinion words and determine their semantic orientation [15]. The process can be carried out at three levels which are document level, sentence level, and aspect level. The document and sentence level yielded the overall opinion of the document or sentence. On the other hand, the aspect sentiment level extracts different aspects and opinions associated with each aspect of the given entity [14]. The aspect extraction is the major step in sentiment analysis at aspect level. For example, the sentence "*The phone has great buttons but the speaker is very bad"* consists of two aspects. The first aspect is *buttons* with positive opinion, and the second aspect is *speaker* with negative opinion. In this example, the extracted aspects are mentioned explicitly. However, given a review statement, *"The phone is cheap",* the word *cheap* is an indicator for an implicit aspect which referring to *price*. Thus, an aspect can be explicit or implicit [1], and an aspect extraction technique to extract such kind of aspects is required.

Currently, there are many techniques proposed in literature for explicit aspect extraction, however, very limited works are reported on implicit aspect extraction [16]. In this paper, we proposed new approaches for both explicit and implicit aspect extraction. For explicit aspect extraction, we proposed to use new novel metaheuristic algorithm Whale Optimization Algorithm (WOA) [18]. The WOA algorithm will be used to select the best combinations of patterns from the set of created patterns. Lastly, Normalized Google Distance (NGD) will be used for aspect pruning. For the second extraction task, to extract implicit aspect, we proposed a hybrid approach, which utilize the co-occurrence between the extracted explicit aspects and their opinion words, dictionary

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for opinion words that rarely cooccur together, NGD for check the candidate aspects.

The rest of paper is organized as follows: Section II presents the related works, section III explains the proposed extraction techniques, section IV presents the discussion on the proposed techniques, and finally section V concludes the whole paper.

II. RELEATED WORK

A. Explicit aspect extraction

Recently, studies on aspect extraction for sentiment analysis has been conducted by many researchers. In the early work conducted by Hu & Liu [1], frequent noun and noun phrases were extracted as candidate aspects. These extracted frequent nouns and noun phrases were then be used to extract their related adjective opinion words. Finally, these opinions words will be used to extract infrequent aspects. In a study done by Samha [2], the aspects were extracted based on a set of manually created dependency relations rules. The created rules are based on observation from the used dataset. In addition, these rules were combined with the used of subjective lexicon, however, their work did not cover all the possible rules.

Qiu, et al. [3] proposed double propagation algorithm for aspect and opinion words extraction. At the beginning, the algorithm requires seed words to start the propagation process. Also, they defined propagation rules based on the use of dependency relations. These defined syntactic relations were created by exploiting the available syntactic relations between word in the reviews. The seed words used to extract features and opinion words by utilizing the defined propagation relations. They used these new features and opinion words to extract new features and opinion words. However, this approach suffers from propagation errors, did not cover all possible syntactic relations and did not manage to extract features that are not related to opinion words or implicit features. In another study, two algorithms for rule selection, which are Simulating Annealing and Greedy algorithm, were being proposed [4]. However, they did not include aspects pruning and the Simulating Annealing algorithm used in this work can leave the optimal solution without returning to it. In addition, they also did not handle the implicit aspect extraction.

In [5], they extracted explicit aspect based on the use of rule based approach by define set of rules based on dependency relations between words and common-sense knowledge. Moreover, in [6] they proposed the use of different types of dependency relations for extracting product features. These rules used combination of different dependency relations to extract features and its related opinion words.

B. Implicit aspect extraction

In the previous study done by Hai et al. [7], an approach to extract implicit features, which based on the co-occurrences frequency matrix between the extracted explicit features and their opinion words was proposed. A set of association rules based on the created co-occurrence matrix was built. Rana & Cheah [8] proposed to extract implicit features based on the co-occurrences between the explicit features and their related opinion words. In addition, they used Normalized Google Distance (NGD) to find the similarity between the candidate implicit feature and the opinion word. However, they didn't consider context of the sentence and relied only on the used corpus.

Fei et al. [9] extracted implicit features based on dictionary, which was created by selecting number of opinion words where for each opinion word its glosses were extracted from online dictionaries. Then, the noun words are extracted from these glosses as potential implicit features candidates, but the corpus are not combined in the calculations. According to Hai et al. [10] implicit features are extracted based on clustering approach. They grouped explicit features into number of clusters by using K-means algorithm. In addition, the opinion words, which related to the features of the given cluster are all included.

III. PROPOSED APPROACH

In this section, we explain about the overall proposed approach which is divided into two tasks: 1) explicit aspect extraction; and 2) implicit aspect extraction.

A. Explicit aspect extraction:

The explicit aspect extraction task is divided into the following tasks as shown in Fig. 1.

- Data preparation and dependency relations rules extraction: In this step, we process all reviews related to the used datasets by removing all un-necessary characters and special symbols. In the next step, we identify each sentence boundary to use it for further processing. Moreover, we execute Stanford parser to find available dependency relations on the identified sentences. The dependency relation is a grammatical relationship between two words, which are head and dependent word [17]. The used hand-crafted dependency rules are from two sources which are from the previous studies [2,3,5,6], and from other new rules by observing datasets to find uncovered rules in the previous studies. The rules considered not only adjective as opinion words, but also other POS types such as noun and verbs. The following Table 1 presents subset of the used rules, and not all rules are written based on the limited space available as there are many more rules.
- Whale Optimization Algorithm for rule selection (WOA) is a newly bio-inspired metaheuristic algorithm, which proved its search capability in comparison with the other famous optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The search methodology proposed in WOA is based on mimicking the hunting behavior used by humpback whales to catch its prey [18].

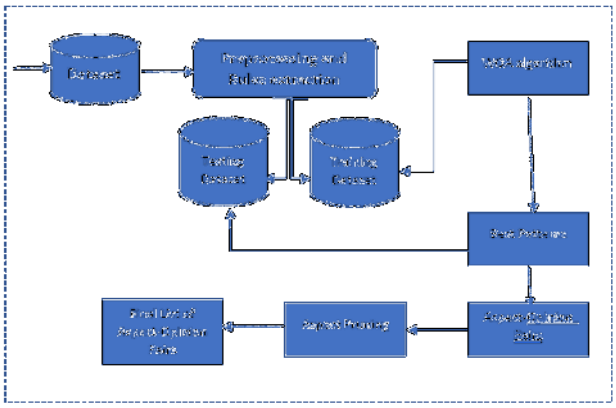

Fig.1: Explicit aspect extraction

TABLE 1: SUBSET OF USED PATTERNS IN THE RULE SELECTION

Pattern used	Example
dobj(like, screen)	I/PRP like/VBP the/DT screen/NN of/IN this/DT phone/NN The extracted aspect "screen" and the opinion word "like"
amod(weight, good) conj(weight, size)	good/JJ weight/NN and/CC size/NN The extracted aspects "weight" and 'size" and the opinion word for each aspect is "good"
dep(nice, focusing)	nice/JJ focusing /VBG The extracted aspect " focusing " and the opinion word "nice"
xcomp(looks, nice)	looks/VBZ nice/JJ The extracted aspect "looks" and the opinion word "nice"
amod(pictures, high) compound(pictures, quality)	high/JJ quality/NN pictures/NNS The extracted aspect "pictures quality" and the opinion word "high"
compound(quality, buttons) nsubj(nice, quality)	The/DT buttons/NNS quality/NN is/VBZ very/RB nice/JJ
amod(screen, large) amod(screen, bright)	large/JJ bright/JJ screen/NN The extracted patterns (large , screen) and (bright, screen)
nsubj(extraordinary, display) conj(display, brightness)	The/DT display/NN and/CC brightness/NNS in/IN this/DT phone/NN is/VBZ quite/RB extraordinary/JJ The extracted patterns (extraordinary, display) and (extraordinary, brightness)
amod(recording, video) nsubj(limited, recording)	video/JJ recording/NN is/VBZ limited/JJ The extracted pattern (video recording, limited)

- The hunting mechanism by creating a stream of bubbles in circle shape or '9'-shaped track' around the prey as the whale is moving in spiral way from down up to the surface. The humpback whale bubble-net feeding mechanism which included the creation of bubbles and encircling the prey is the key motivation for building WOA algorithm. In WOA algorithm the bubble-net feeding mechanism was formulated as a mathematical model and divided into three mainly phases which are: Encircling prey, Exploitation (bubble-net attacking), and Exploration (search for prey). The pseudocode for WOA algorithm is shown in Fig. 2 [18].

- Encircling prey phase: In this phase, there are number of search agents (whales) trying to detect the prey location and encircle them. Moreover, the WOA algorithm at this phase try to find the best search agent, which is near the optimal solution or it is the prey itself. After the best candidate search agent identified then WOA update other search agents (whales) positions toward the current best agent according to the following equations:

$$\vec{D} = |\vec{C}.\vec{X^*}(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X^*}(t) - \vec{A} \cdot \vec{D} \quad (2)$$

where the variables are A and C represents coefficient vectors and the variable X^* represents the position vector of the best solution obtained so far, X is the position vector. In addition, WOA algorithm update the best position vector at the end of each iteration if it finds better solution. Also, t points to the current iteration and A and C are determined by using the following equations:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (4)$$

```
Initialize the whales population Xi(i = 1, 2, 3, ..., n).
 Find the fitness of each whale.
 X*=best whale.
 while (t < maximumnumberofiterations) do
        for (eachwhale) do
        Update a, A, C, l and p.
                if (p < 0.5) then
                        if (|A| < 1) then
                        Update whale position by Eq (1)
                        else if (|A| ≥ 1) then
                                Select a random whale Xrand.
                                Update position of current
                                whale by Eq(7)
                        end
                else if (p ≥ 0.5) then
                        Update position of current whale by Eq(5).
                end
        end for
        Check if any whale goes beyond the search space and amend it.
        Find the fitness of each whale.
        Update X* if there is a better solution.
        t = t + 1
 end while
 return X*
```

Fig.2: Whale Optimization Algorithm [18]

where a is linearly decreased from 2 to 0 over the iterations and r is a random vector in [0,1].

- Bubble-net attacking phase (Exploitation): represented by two approaches as the following:
  1. Shrinking encircling mechanism: the main objective of this approach to decrease the value of a linearly from 2 to 0. Also, vector A assigned random values over the range [-1,1].
  2. Spiral updating position: In this phase WOA determine the distance value between the whale position and the prey position. Then, they defined an equation (5) based on the distance between whale position and prey position to model the spiral movement of the humpback whales by using the following equations, where b variable is a constant value used to define the shape of logarithmic spiral

$$\vec{X}(t+1) = \vec{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X^*}(t) \quad (5)$$

- Search for prey phase (Exploration): In this phase WOA algorithm switch between exploitation and exploration based on A vector value, which mean if the random value of $|A|<1$ the search agents (whales) update their positions with reference to the best selected search agent so far (exploitation) and do local search, while if $|A|\geq 1$ the search agents update their positions with reference to the randomly selected agent(exploration) to do a global search according to the following equations:

$$\vec{D} = |\vec{C} \cdot \overrightarrow{X_{rand}} - \vec{X}| \quad (6)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \quad (7)$$

Where X_{rand} is a random position vector value for the selected agent from the current population.

- Rule patterns selection using WOA: The WOA algorithm is selected based on its capability of local search and global search and the balance between the two tasks. WOA is applied adaptively on the rules set to find the optimal rule subset combination that maximize the F-measure, the workflow of the proposed rule selection using WOA as the following steps:
  1. The dataset is divided into two parts training set (TR) and testing set (TS).
  2. Set of all rules which included the new created rules and the rules used from previous studies will be used and called *Rset.*
  3. WOA initialization step: which include randomly generating number of possible solutions based on the specified number of agents(whales) n. (where each agent represents a possible solution, and include a randomly selected subset of rules from *Rset*).
  4. Agent fitness evaluation: For each search agents calculate it fitness value using F-measure on TR according to the selected rules in the current agent.
  5. Update search agents' position.
  6. Repeat step 4 and 5 until WOA reach the maximum number of iterations t.
  7. Finally, the optimal set of rules which resulted from WOA with maximum F-measure will applied to TS. Moreover, the list of extracted explicit aspects and opinion words from this step will be used in next step (aspect pruning).
- For example, assume that the number of rules in *Rset* is equal to 50, number of whales is specified by 10 and number of iteration 20. Then, after applying WOA on TR using Rset it will generate 10 possible solutions from Rset in the initialization phase of WOA with each solution contain some randomly selected rules from *Rset*. Moreover, for each solution in the 10 generated solutions the F-measure will be calculated to find the fitness value for each whale. Now, the algorithm repeats steps 4 and 5 until it will arrive at max number of iteration for example 20 iterations. At the final phase, the optimal whale will be considered and its selected rules represent the optimal rules to be applied on the TS.
- Extracted features refinements and pruning: In this phase, the following steps are used:
  1. From the extracted explicit features in the previous step take the frequent features and discard the non-frequent features.
  2. Add to selected features in step 1 the product specifications from the products website.
  3. Apply semantic relations on the resulted features in step 2 by using WordNet to find the synonyms and meronyms (part of relation) and add the result to the result of step 2 and call the result domain features (DF).
  4. Now find the synonyms of domain entity and add it to domain entity and call it DEALL.
  5. Find the similarity between every word in DEALL and every non-frequent feature discarded in step 1 using (NGD). In this step only features that have similarity with any term in DEALL less than a selected threshold will be taken for next steps, else we calculate NGD between the feature and every feature in step 3 and if NGD less than prespecified threshold with any feature in 3 we approve the feature otherwise we will discard it.
  6. Now Take the frequent features and their opinion words. In addition, the approved non-frequent features, and their related opinion words.
- Normalized Google Distance (NGD): NGD used to find relatedness (cooccurrence) between two words based on web search (Google) by using the following equation (8), where f(x,y) return the number of web pages contains both x and y, f(x) is the number of returned

pages which contain x, f(y) number of returned pages which contain y, and N is the total number of pages indexed by Google. The values returned from applying NGD are between 0 and infinity. The value of 0 means that both terms x and y always cooccur together in the webpage, but if the terms never cooccur together within the same page its NGD equal infinity [11].

$$\mathrm{NGD}(x,y) = \frac{\max\{\log f(x), \log f(y)\} - \log f(x,y)}{\log N - \min\{\log f(x), \log f(y)\}} \quad (8)$$

B. Implicit aspect extraction

In this phase, the implicit extraction is performed using a hybrid approach by utilizing both corpus based approach and dictionary based approach according to the following steps to take the advantages of both approaches as presented in Fig.3:

- Step1: Create a cooccurrence frequency matrix between every extracted explicit aspect and their opinion words and call this matrix M.
- Step2: add to M matrix the cooccurrence between the opinion word and other notional words in the sentence
- Step 3: add to M matrix the cooccurrence between notional words itself.
- Step 4: for each opinion word in M use WordNet to find its antynoms and synonyms. (this step required as sometimes the explicit feature cooccur with an opinion word such as "*high*", but the current word without an explicit feature is "*low*" the antonym of "*high*" word, then by the feature cooccur with "*high*" we can know also the feature that cooccur with "*low*" words as it's the word antonym).
- Step 5: for each opinion word in opinion lexicon [1] as performed in [9] find its glosses nouns from the online dictionaries and store these noun with opinion words dictionary D. also in our work is different as we consider the semantic relations of each opinion word. (this step required to make the implicit aspect identification not based only at corpus as step 1).
- Step 6: for each opinion word without an explicit aspect do the following steps (Call the opinion word without an explicit aspect OIA):
  - Search for OIA (the OIA word or its synonyms or its antynoms) found in M matrix then take its cooccurred aspects as possible candidate aspects.
  - Search for OIA (the OIA word or its synonyms or its antynoms) the dictionary D and retrieve its cooccurred nouns as possible candidate aspects.
- Step 7: In this step from the selected candidate implicit aspects in step 6 do the following:

  1. Now for each candidate aspect in CIA find its similarity to the notional words in the implicit sentence context for OIA by using NGD and take

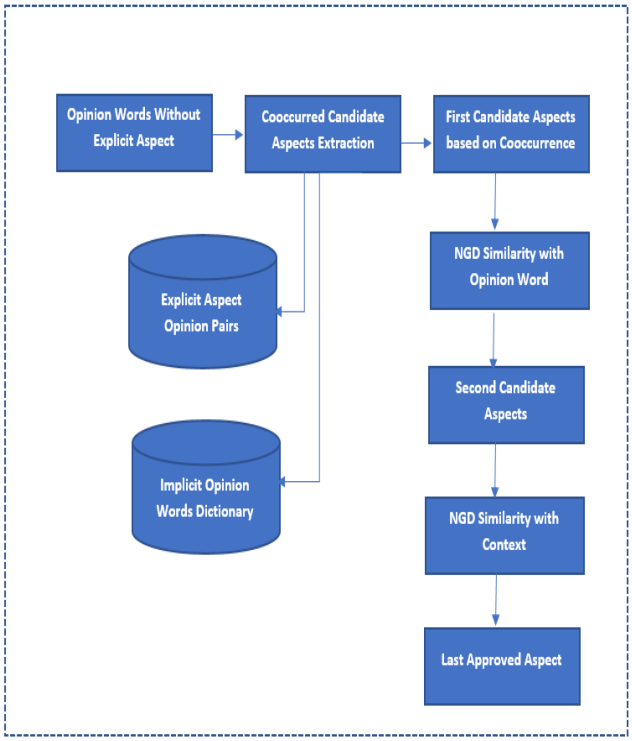

Fig.3: Implicit aspect extraction

the best CIA aspect according to NGD value as the potential implicit aspect. (this step required as sometimes one aspect has the best NGD value with the OIA word, but this aspect not related to the opinion word context (notional words), so we must check the compatibility of the candidate implicit aspect with its context).

2. If no notional words exist in the implicit sentence context, then find NGD between the CIA and the notional word in the sentence that have the same OIA word. In addition, take the best CIA aspect according to NGD value as the potential implicit aspect.

Else: Find similarity between each candidate aspect and the OIA using NGD and the best CIA aspect according to NGD value as the potential implicit aspect. Moreover, check the compatibility of the candidate implicit aspect with the domain entity to make double check by find NGD between the candidate aspect and domain entity and if it less than specified threshold take it; otherwise find NGD between the candidate aspect and frequent explicit aspects and if it less than specified threshold with any one take it; otherwise discard it.

IV. DISCUSSION

In this work, instead of using a small set of dependency relations rules to extract the explicit aspects and their related opinion word, we used all possible relations rules from the previous studies and newly created rules patterns created by

observing the reviews. We also used WOA algorithm to select the optimal combination from these rules because the use of all rules decreases the extraction performance. WOA is chosen as it has a good balance capability between exploitation and exploration. It starts with number of possible solutions and search locally and globally for optimal solution. In addition, an outstanding web based similarity measure NGD was used for pruning by taking the possible cases such as the relation between the discard features and domain entity and its synonyms or with frequent extracted features or product specifications features.

In the previous work conducted in [12], NGD was only found between the domain entity and non-frequent noun features, however, in our approach, we calculate for other non-frequent features types such as verb features, and noun phrase features. We also find the synonyms of the domain entity as the customers may write the domain entity word using different synonyms such as "*Phone*", "*Cell Phone*", "*Mobile*", and so on. In addition, we find the NGD between discard non-frequent features and each frequent feature and product specification features.

In implicit aspect extraction, most of the previous works are based on the used corpus without any other sources. Our work is closely related to the previous work [8], however, we do not based only on the corpus for implicit aspect extraction, but also combined it with the dictionary based approach. In addition, using our approach, we could find the semantic relations of the opinion words. Thus, we could improve the co-occurrence matrix with the cooccurrence between the notional words and opinion words and between notional words itself. We calculate NGD not only between the opinion word and candidate features but also with the notional words in the implicit sentence context. If we based only on NGD between opinion word and candidate implicit features, the algorithm will select a feature that are not related to the given implicit context. Thus, it is important to check the correctness of the selected feature by finding its NGD with the notional words in the implicit sentence since notional word improves the implicit extraction process as in [13].

V. CONCLUSION

With the rapid expansion of the internet and E-commerce websites, and huge number of users using these websites make the sentiment analysis become a challenging research area. Sentiment analysis can give more insights to new customers or manufacturers based on the previous customer experiences and feedbacks.

The growth of sentiment analysis has resulted in the emergence of various techniques for explicit aspect extraction and implicit aspect extraction. However, most of the techniques conducted for aspect extraction, either for explicit aspect or implicit aspect extraction, but none for both. In addition, most of the works which based on either frequent patterns or dependency rules use the whole set of patterns or rules without selecting the best subset of patterns or rules for aspect extraction. Thus, in this paper, we propose to use a hybrid approach for both tasks, the explicit aspect extraction task and implicit aspect extraction task. We are working on implementing the proposed approaches and testing them over standard datasets. For future work, we would also like to consider applying WOA on implicit aspect extraction.

REFERENCES

[1] M. Hu and B. Liu. “Mining and summarizing customer reviews”. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, pp. 168-177, 2004, August.

[2] A. K. Samha. “Aspect-based opinion mining using dependency relations”. In IJETA 2016: International Journal of Engineering Trends and Applications, Feb 2016.

[3] G. Qiu, B. Liu, J. Bu, and C. Chen. “Opinion word expansion and target extraction through double propagation”. Computational linguistics, 37(1), 9-27, 2011.

[4] Q. Liu, Z. Gao, B. Liu, and Y. Zhang. “Automated rule selection for opinion target extraction”. Knowledge-Based Systems, 104, 74-88, 2016.

[5] Poria, S., Cambria, E., Ku, L. W., Gui, C., & Gelbukh, A., “A rule-based approach to aspect extraction from product reviews”, in Proceedings of the second workshop on natural language processing for social media (SocialNLP), pp. 28-37, 2014, August.

[6] V. R. Kumar and K. Raghuveer. “Dependency driven semantic approach to product features extraction and summarization using customer reviews”. In Advances in Computing and Information Technology, Springer, Berlin, Heidelberg, pp. 225-238, 2013.

[7] Z. Hai, K. Chang, and J. J. Kim. “Implicit feature identification via co-occurrence association rule mining”, in International Conference on Intelligent Text Processing and Computational Linguistics, Springer Berlin Heidelberg, pp. 393-404, 2011, February.

[8] T. A. Rana and Y. N. Cheah. “Hybrid rule-based approach for aspect extraction and categorization from customer reviews”. In IT in Asia (CITA), 2015 9th International Conference on IEEE, pp. 1-5, 2015, August.

[9] G. Fei, B. Liu, M. Hsu, M. Castellanos, and R. Ghosh. “A dictionary-based approach to identifying aspects implied by adjectives for opinion mining”. In 24th international conference on computational linguistics, p. 309, 2012, December.

[10] Z. Hai, K. Chang, G. Cong, and C. C. Yang. “An Association-Based Unified Framework for Mining Features and Opinion Words”. ACM Transactions on Intelligent Systems and Technology (TIST), 6(2), 26, 2015.

[11] R. L. Cilibrasi and P. M. Vitanyi. “The google similarity distance”. IEEE Transactions on knowledge and data engineering, 19(3), 2007.

[12] T. A. Rana and Y. N. Cheah, “A Two-Fold Rule-Based Model for Aspect Extraction”, Expert Systems with Applications, 2017.

[13] Y. Zhang and W. Zhu. “Extracting implicit features in online customer reviews for opinion mining”. In Proceedings of the 22nd International Conference on World Wide Web, ACM pp. 103-104, 2013, May.

[14] W. Medhat, A. Hassan, and H. Korashy. “Sentiment analysis algorithms and applications”: A survey. Ain Shams Engineering Journal, 5(4), 1093-1113, 2014.

[15] B. Liu and L. Zhang. “A survey of opinion mining and sentiment analysis”. In Mining text data, Springer US, pp. 415-463, 2012.

[16] T. A. Rana and Y. N. Cheah. “Aspect extraction in sentiment analysis: comparative analysis and survey”. Artificial Intelligence Review, 46(4), 459-483, 2016.

[17] M. C. Marneffe and C. D. Manning. “Stanford typed dependencies manual. Technical report, Stanford University”, pp. 338-345, 2008.

[18] S. Mirjalili and A. Lewis. “The whale optimization algorithm”. Advances in Engineering Software, 95, 51-67, 2016.